The (in)stability of farmers' risk preferences

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Abstract

We test and quantify the (in)stability of farmer risk preferences, accounting for both the instability across elicitation methods and the instability over time. We used repeated measurements (N=1530) with Swiss fruit and grapevine producers over 3 years, where different risk preference elicitation methods (domain-specific self-assessment and incentivized lotteries) were used. We find that farmers' risk preferences change considerably when measured using different methods. For example, self-reported risk preference and findings from a Holt and Laury lottery correlate only weakly (correlation coefficients range from 0.06 to 0.23). Moreover, we find that risk preferences vary considerable over time too, *i.e.* applying the same elicitation method to the same farmer in a different point in time results in different risk preference estimates. Our results show self-reported risk preferences are moderately correlated (correlation coefficients range from 0.42 to 0.55) from one year to another. Finally, we find experiencing climate and pest related crop damages is associated with farmers becoming more risk loving.

Keywords Risk preferences, stability, agricultural shocks

JEL code C90, D81, Q12

Introduction

Uncertainty and risk are essential elements of agricultural production. Thus, farmers' risk perception and risk preferences are key elements of their decision-making (Just and Just, 2016). Knowledge about farmers' risk preference is of great importance for policy and industry. For example, accurate predictions about farmers' decisions and their responses to market and policy changes need to consider risk preferences. Agricultural economists use a wide range of methods to elicit farmers' risk preferences, ranging from self-reporting using surveys, econometric and mathematical methods to a large spectrum of incentivized lotteries (Iyer et al. 2020, Charness et al., 2013). There is no risk preference elicitation method that dominates all others. A major problem is that risk preference elicitation often results in non-stable results. This instability can have two explanations. First, risk preferences may change when measured using different methods (Pedroni et al. 2017, Berg et al. 2005). Thus, applying different elicitation methods at the same time to the same farmer may result in different, even reversed, conclusions on their risk preference[1]. Second, risk preferences can vary over time *(Schildberg-Hörisch,* 2018). Thus, applying the same elicitation method to the same farmer in a different point in time may result in different estimates for their risk preferences. The instability of risk preferences challenges the assumption of perfect stability in neoclassical economic theory and poses a challenge for the use of these results in economic and policy analyses. The relevance, magnitude and causes of these instabilities in farmer risk preferences remain, however, not well known.

In this paper, we provide a new quantification of the (in)stability of farmer risk preferences, accounting for both the instability across elicitation methods and the instability over time. We also compare the relevance of both sources of instability and explore origins of temporal instability of risk preferences. To this end, we use repeated risk preference measurements with Swiss farmers and test if experiencing yield losses cause farmers to be more or less risk averse in subsequent periods.

Previous economic and psychology research has shown that measured risk preferences are sensitive to the elicitation method (e.g. Pedroni et al. 2017, Berg et al. 2005). For example, Pedroni et al. (2017) challenge the view that different elicitation methods manage to stably capture risk preference. In contrast, risk preferences may be constructed when they are elicited, and different cognitive processes can lead to varying preferences. Thus, different contexts and domains underlying the elicitation methods change the identified risk preference (Berg et al. 2005). Previous research also documented that risk attitudes vary over time. Thus, applying the same elicitation task with the same individual in different periods results in different risk preferences (e.g. *Schildberg-Hörisch,* 2018, Anderson and Mellor, 2009, Andersen et al. 2008). This may reflect noise in the measurement procedure, but also may be explained by the experience of shocks. For example, exposure to hurricanes, earthquakes and floods have been shown to cause changes to peoples' risk preferences (e.g. Eckel et al. 2009, Page et al. 2014,

[1] Note that there is a rich general literature on risk preference elicitation, inconsistencies and instability across elicitation methods, e.g. Abdellaoui et al (2011), Andersen et al. (2006, 2010), Dave et al. (2010), Engle-Warnick et al (2009), Fausti and Gillespie (2006), Hardeweg et al (2013), Maart-Noelck and Musshoff (2014), Menapace et al. (2016), Nielsenet al. (2013), Pennings and Garcia (2001), Verschoor et al. (2016).

Hanaoka et al., 2018, Kim and Lee, 2014, Meier 2022).. Ambiguous direction of effects have been reported, i.e. experiencing shocks (losses) may lead to higher risk aversion (e.g. Bozzola and Finger, 2021, Kim and Lee, 2014) but also more risk loving behavior (e.g. Eckel et al., 2009, Hanaoka et al., 2018). Reasons why perceiving shocks may lead to changes in risk preferences can be, among other, changes in emotions (Meier 2022).

The empirical evidence for both across-method and temporal (in)stability of farmer risk preference is rare. For example, Reynaud and Couture (2012) use different lotteries for a sample of French farmers and show that risk preference measures are not perfectly correlated. There are also only a few applications investigating the temporal stability of farmers risk preferences. For example, Love and Robison (1984) elicit risk preferences of 23 US farmers in two years and conclude that risk preferences are not stable over time. Koundouri et al. (2009) show that Finnish farmers became less risk averse after Finland's EU accession and inclusion in the Common Agricultural Policy. Bozzola and Finger (2021) use a 21-year record of farm-level panel data from Italy and show that risk preferences change over time. Yet, studies have either focused on temporal stability or stability across elicitation methods. Thus, it is unclear how relevant the magnitude of either source of instability is for risk preference elicitation. Moreover, temporal instability of farmers' risk preferences has so far relied on either very small samples (Love and Robison 1984) or on econometric estimation of risk preferences using the *method of moments* approach (Koundouri et al., 2009, Bozzola and Finger, 2021), which faces challenges for identification of (changes in) risk preferences (e.g. Just and Just, 2016). Finally, no domain specific assessment of risk preferences due to shocks has been conducted.

We here contribute to the literature on the (in)stability of farmer risk preferences and provide an analysis accounting for both the instability across elicitation methods and the instability over time. To this end, we used repeated measurements with Swiss fruit farmers over 3 years (2016-2018) and a total number of 1530 observations. We use repeated measurements of self-reported risk preferences in 4 different domains, as well as a Holt and Laury lottery for the year 2018. We also investigate underlying mechanism in temporal instability of risk preferences. More specifically, we exploit shocks due to crop losses caused by an invasive pest (Drosophila suzukii) as well as damages to fruits and vineyards caused by severe frost events.

We find that i) self-reported risk preferences across different domains are highly correlated (correlation ranges up to 0.72) but this correlation differs considerably across domains and time, ii) self-reported risk preference and findings from the Holt and Laury Lottery correlate only weakly (correlation coefficients range from 0.06 to 0.23), iii) self-reported risk preference are moderately correlated (correlation coefficients range from 0.42 till 0.55) from one year to another, iv) and this correlation decreases further if focusing on risk preferences measured with a time differences of two years (correlation coefficients decreases from 0.20 to 0.48), v) the experience of individual shocks has only limited effects on farmer risk preferences. But the experience of both frost and pest related damages tends to cause farmers to be more risk loving.

The remainder of this article is structured as follows. Next, we present details on the survey, risk preference elicitation methods and econometric analysis. Then, we present and discuss results. Finally, we conclude.

Methods

We combine results from repeated online surveys undertaken with plum, cherry and grapevine producers in Switzerland from 2016 to 2018. In total 8 surveys have been conducted. For plum and grapevine producers, surveys were conducted in 2016, 2017 and 2018. For cherry producers, surveys were only conducted in 2017 and 2018. The covered crops are economically highly relevant for Swiss agriculture, i.e. the production of fruit and grapes for wine production together represented 11% of the total agricultural production value in 2018 (e.g. Knapp et al., 2021a). We used an online questionnaire ran via Limesurvey. The survey, including the risk preference elicitation tasks, was pre-tested and piloted with farmers. A link to the survey was provided to farmers by email, shared via their cantonal agricultural services, as well as via newsletters and information material sent to them. Once farmers participated, we also directly addressed them in subsequent years via email with an invitation to participate in new surveys. Clicking the provided link, farmers could choose to answer in German, French or Italian, i.e. the main languages spoken in Switzerland. In total, we here use 1530 observations, but face an unbalanced panel structure of our data. Our sample represents approximately 10% of Swiss plum and cherry farmers and about 21% of total Swiss grape farmers. Characteristics of farmers and the farms in the samples are overall in line with the Swiss population of producers of these crops at large (see Knapp et al., 2019, 2021a). The main purpose of the survey was to study farmers risk management, especially in terms of management of an invasive species (Drosophila suzukii) and other risks (see Knapp et al., 2021a,2021b, Wuepper et al., 2021 for further applications). The data is freely accessible, see Knapp et al. (2019) for further documentation of details on the surveys.

Risk preferences were first elicited using contextualized self-assessment questions on attitudes towards risk taking in four different domains (production, market and prices, external financing and agriculture in general) (following e.g. Weber et al. 2002, Meuwissen et al., 2001). A 11-point Likert scale assessment question was used following Dohmen et al. (2011). Higher numbers correspond to more risk averse decision makers (see Iyer et al. 2020, for an overview of further applications)[2]. The detailed questions are presented in Appendix A. In 2018, we also used an incentivized multiple price list following Holt and Laury (2002)[3]. The lottery task was following closely to the initial setup and was contextualized, i.e. we framed the choices in a pest management setting[4] (see Appendix A for details). Participating farmers could win up to 200 CHF (ca. 220$) (see Knapp et al., 2019 and Appendix A for details). We follow Holt and Laury (2002) and use the number of 'safe choices' as an indication for risk aversion, which

[2] The scale used in the survey was actually reversed, but in our empirical analysis presented below, we have inverted this scale, so higher numbers are more risk averse.
[3] There is a large variety of lottery-based approaches to elicit risk preferences (see e.g. Charness et al. 2013, Iyer et al 2020). We here opted for the Holt and Laury lottery because it is widely used and straightforwardly implemented. Further research shall use a wider range of methods for risk preference elicitation.
[4] This context specific framing of the lottery contributes to fewer noise in the risk preference elicitation (following e.g. Meraner et al. 2018, Rommel et al., 2019).

results in an outcome on a range from 0 to 9, with higher numbers being more risk averse (see Appendix A for corresponding levels of Arrow-Pratt coefficients of risk aversion)[5].

Our analysis starts with presenting correlations of risk preferences across the different elicitation methods, i.e. across different self-stated domain specific risk preferences as well as for the Holt and Laury lottery. This allows us to test the instability of farmer risk preferences across elicitation methods and domains. Next, we present correlations of risk preferences across years for all self-stated domain specific risk preferences. In these steps, we pool data from different surveys, i.e. across types of farmers. More specifically, we calculate differences across years (2017 vs. 2016, 2018 vs. 2017, 2018 vs. 2016) in farmers' responses to contextualized self-assessment questions on attitude to risk taking in the four different domains. This step allows us to explore the extent of temporal instability of farmer risk preferences.

After testing for changes in risk preferences over time and quantifying their extent, we also test, whether these changes can be associated with the experience of shocks in production causing yield losses. To this end, we exploit that some of the surveyed farmers faced, in some years large damages to their production. More specifically, we focus on two key sources of yield losses in Swiss fruit and grapevine production.

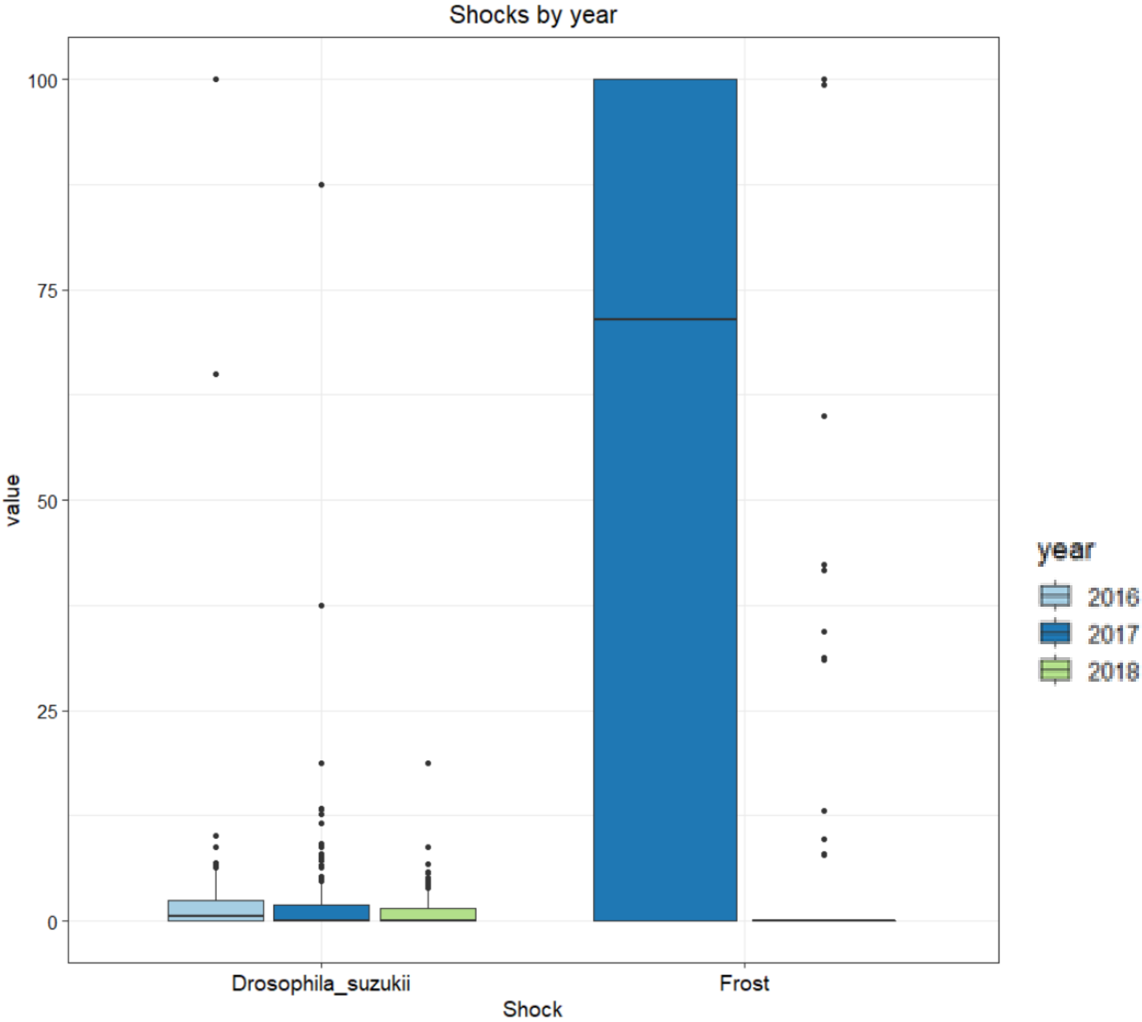
First, we test effects of experiences of frost related damages to fruits and wine. During flowering in spring, late frosts regularly cause large losses in quantity and quality of fruits and vineyards (Vitasse and Rebetez, 2018, Dalhaus et al., 2020). Frost damages were exceptionally large (in terms of intensity and spatial extent) in the year 2017 (Vitasse and Rebetez, 2018). In the survey, farmers were asked to indicate whether they experienced frost damages in the year of the survey. In our sample, more than 60% of producers faced some frost damage in 2017, compared to 6% in 2018 (see Figure 1).

Second, we test effects of experiences of damages due to Drosophila suzukii, an invasive insect pest that emerged rapidly as a major threat to horticultural production in United States and Europe (including Switzerland) in the last decade. *Drosophila suzukii* attacks a wide range of hosts, especially also the here considered crops cherry, grapevines, and plums. Infested fruit is unmarketable due to zero tolerance policies, i.e. infestation affects especially the marketing of crops and leads to large revenues losses (see Knapp et al., 2021a, Walsh et al., 2011, Fan et al., 2020). In the survey, farmers were asked to indicate whether and to what extent they experienced damages due to Drosophila suzukii in the year of the survey. While on average the infestation with Drosophila suzukii is less than 5% of the overall acreage, individual producers face substantial infestations (see Figure 1). We define shocks in our analysis as the percentage of crop damaged by Drosophilia suzukii or by frost in the growing season.

Third, we also consider the combination of both shocks, i.e. we test if the experience of both a frost damage and a damage due to Drosophila suzukii in the same year is associated with a change in risk preferences.

[5] There were only few inconsistent answers, i.e. where participants revealed multiple switching behavior or never switched. In total 17 respondents were removed from the analysis of the Holt and Laury lottery data. See Appendix A for more details.

Figure 1. Summary statistics of Drosophila suzukii and frost damage by year



Note: Frost damages were not collected for 2016, but there was no large frost event in this year.

We explore the association between experiencing production shocks as defined above and changes in risk preferences over time. More specifically, we also explore domain-specific assessments of changes in risk preferences. This allows us to test how, i.e. in which domain, different production shocks affect farmers' risk preferences. To this end, we conduct regression analysis. More specifically, we exploit farmer-level changes in elicited risk preferences from one year to another, i.e. from 2016 to 2017 and 2017 to 2018. We pool these observations across fruits and years and regress it to the farmer-level experience of frost damages (percentage of crop damaged by frost), the experience of damages due to Drosophila suzukii (percentage of crop damaged by Drosophila suzukii) and a combination of both shocks (an interaction term which accounts for frost and Drosophilia suzukii). These shocks are considered for the year of last measurement, i.e. 2017 or 2018. As our survey took place at the end of the year, we expect that experiencing shocks in this year causes changes in risk attitudes. We consider changes in five risk preference measures, i.e. the four specific domains (production, market and prices, external financing and agriculture in general) and an average of these four domains.

The main specification of our estimation is as follows (Equation 1):

$$(1)\ \Delta Risk\ Preference_{it} = \alpha_0 + \alpha_1 Crop\ Damage\ due\ to\ Pest_{it} + \alpha_2 Crop\ Damage\ due\ to\ Frost_{it} + \varepsilon$$

Coefficients α_1 and α_2 show the effect of a 1-unit increase (1 percentage point) in crop damage due to Drosophila suzukii and frost, respectively, on change in risk preferences of farmer i in year t (vis-à-vis year t-1)[6].

Next, we estimate the following model to account for interaction of both shocks (Equation 2):

$$(2) \Delta Risk\ Preference_{it} = \alpha_0 + \alpha_1 Crop\ Damage\ due\ to\ Pest_{it} + \alpha_2 Crop\ Damage\ due\ to\ Frost_{it} + \alpha_3 Crop\ Damage\ due\ to\ Pest_{it} * Crop\ Damage\ due\ to\ Frost_{it} + \varepsilon$$

We present average marginal effects of crop damage due to Drosophila suzukii and frost, respectively, on change in risk preferences of farmer i in year t (vis-à-vis year t-1).

In our main specification, we only consider the variable for shocks (as in Equations 1 and 2).

As robustness checks, we provide additional estimations. First, we also control for year fixed effects, i.e. for the period of measurement (e.g. 2016-2017 or 2017-2018). The latter may capture other changes over time that may affect farmer risk preference but is unrelated to the here considered shocks[7]. Second, we also control for the fruit the farmer produces (i.e. grapevine, cherry, plum). This may account for fruit specific unobserved shocks and changes in samples over time. Again, however, if specific shocks like frost and pest damages have been fruit specific, this inclusion of fruit dummies would result in likely underestimation of the effect of shocks. Third, we also account for farm and farmer characteristics.

Results and Discussion

Figure 2 shows the distribution of elicited risk preferences over years and methods (i.e. domain-specific self-assessment for all years and a Holt and Laury lottery for the year 2018). We find that farmers in our sample are on average risk averse. Yet, there is considerably heterogeneity across individual farmers (see Appendix B). This finding is in line with the majority of risk preference elicitation studies addressing European farmers (cp. e.g. Iyer et al., 2020).

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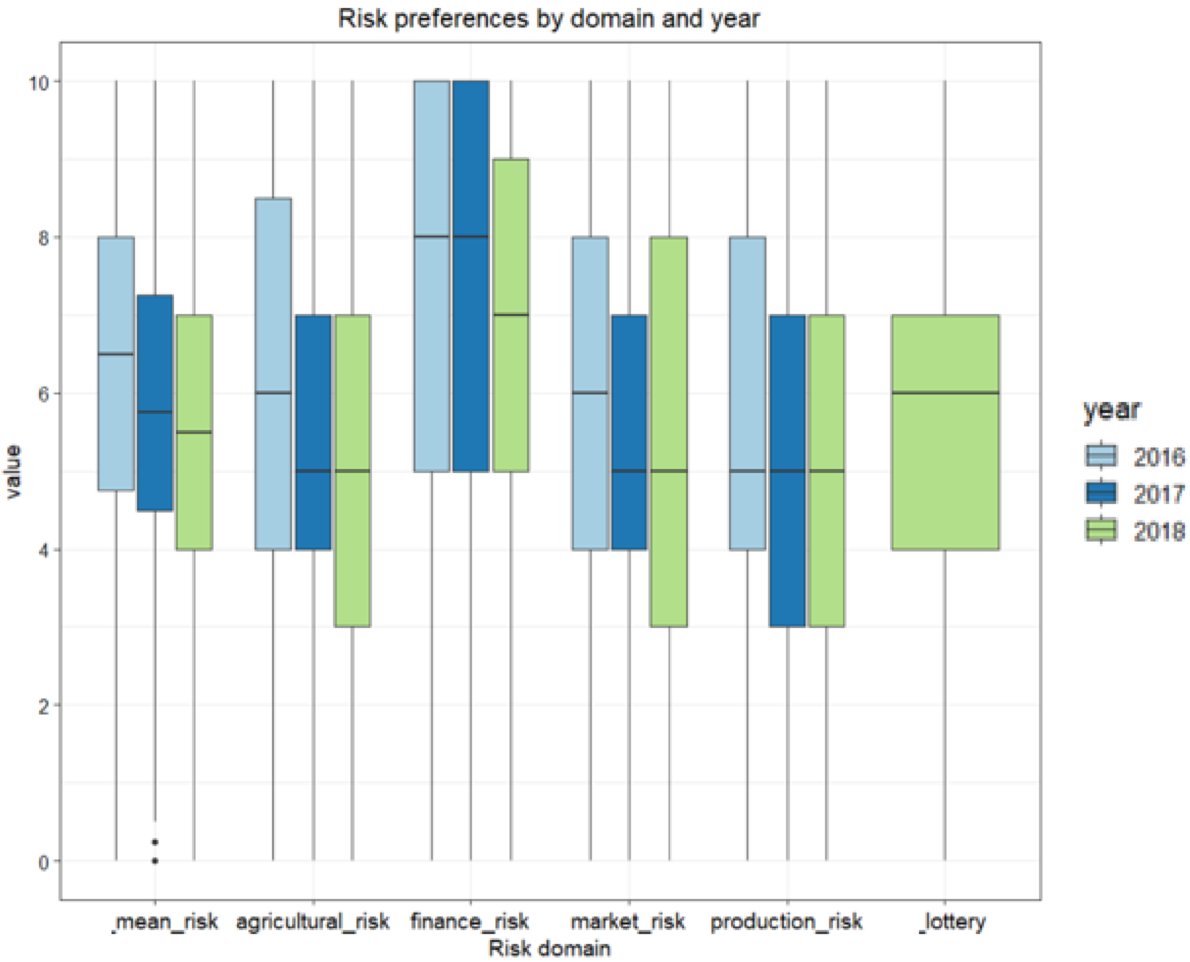
[6] This means that if $\Delta Risk\ Preference_{it}$ is positive (negative), farmer i became more risk averse (loving) from period t-1 to period t.

[7] However, shocks like frost damages have a systemic nature, so that almost the entire country is hit by large scale frost events such as in 2017, which would result in likely underestimation of the effect of shocks in our analysis.

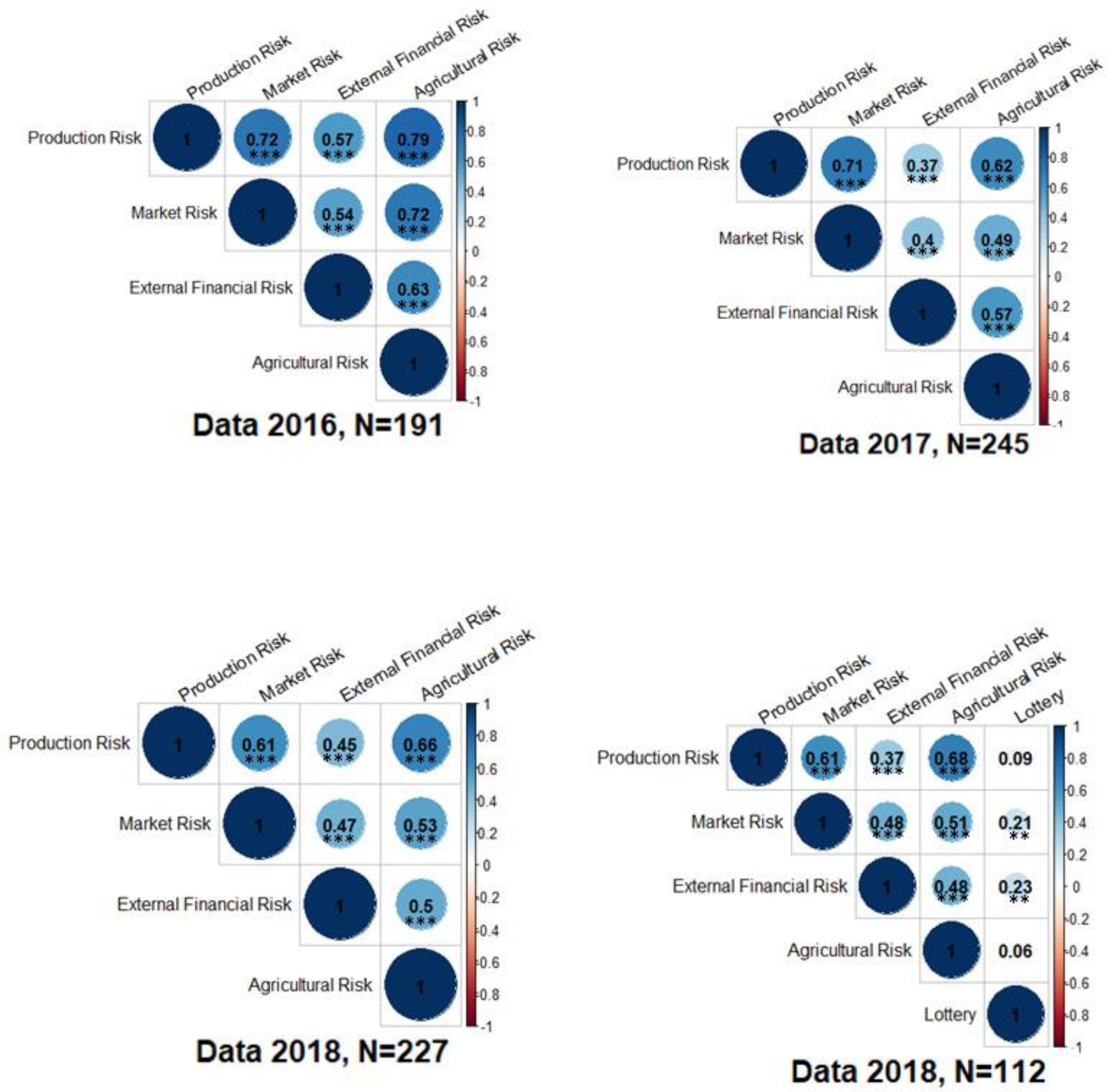
Figure 2. Summary statistics of risk preferences by domain and year



Note: the central line represents the median value; box limits represent the first and third quartiles; the whiskers represent the lower and upper adjacent values; outliers are represented by dots. A value of 5 is risk neutral, <5 is risk loving and >5 is risk averse. For the Holt and Laury lottery we here present the number of 'safe choices' (i.e. on a range from 0 to 9, with higher numbers being more risk averse) as an indication for risk aversion.

Figure 3 presents correlations of risk preferences across different elicitation methods, i.e. across different self-stated domain specific risk preferences as well as across the lottery outcomes for the year 2016, 2017 and 2018 (lottery only on 2018). It shows that self-reported risk preferences across different domains are highly correlated (correlation coefficients up to 0.72) but this correlation differs largely across domains and time. Especially, production, marketing and general agriculture domains seem to be highly correlated with each other, while the external financial risk domain stands out. That is, farmers risk aversion in domains production, marketing and agricultural in general is not necessarily a good predictor for their risk preferences with respect to financial decisions. This highlights the necessity for domain specific analysis of risk preferences. Moreover, we find that self-reported risk preference and findings from the Holt and Laury Lottery correlate only weakly (correlation coefficients 0.06 to 0.23). More specifically, we find a higher correlation between the results from the lottery task and the results from the self-stated risk preference in the external financial risk domain. The low correlation between stated (self-report) and revealed (lotteries) preference measures is in line with the literature on non-farming communities (cp. Mata et al. 2018). Even though the lottery in our analysis was contextualized in an agricultural production setting, it may rather reflect farmers risk preferences in financial domains (as the payouts were financial).

Figure 3. Correlations of risk preferences across different elicitation methods for the years 2016, 2017 and 2018 (with and without lottery task).



Note: ***, ** and * represent that the Null hypothesis of zero correlation is rejected at the 1%, 5% and 10% level of significance, respectively.

Figure 4 shows correlations of risk preferences across years for all self-stated domain specific risk preferences. Note that the number of available observations is smaller in Figure 4, because we a) take differences between risk preferences and b) our panel is unbalanced so that farmers also necessarily participate two or even three years. It shows that self-reported risk preferences are moderately correlated (correlation coefficients from 0.42 to 0.55) from one year to another. This correlation decreases if focusing on risk preferences measured with a time differences of two years (correlation coefficients from 0.20 to 0.48). The temporal stability of risk preferences was found to be highest for the production risk domain, and weakest in the marketing risk domain (Figure 4). In general, our findings are in line with earlier findings for non-farming communities. For example, Mata et al. (2018) present a meta-analysis of test-retest stability of risk preferences.

In general, our results show that the instability of risk preferences across years may be even more severe than instability across elicitation methods. Yet, the difference between self-reported and lottery task derived risk preferences is larger than differences in risk preferences across years within self-reported risk preferences. Note, however, that differences in correlations could also just reflect structural differences between tasks (i.e., that some tasks are somewhat noisier). We re-run all estimations using Spearman rank correlations (instead of Pearson correlations) and find similar results.

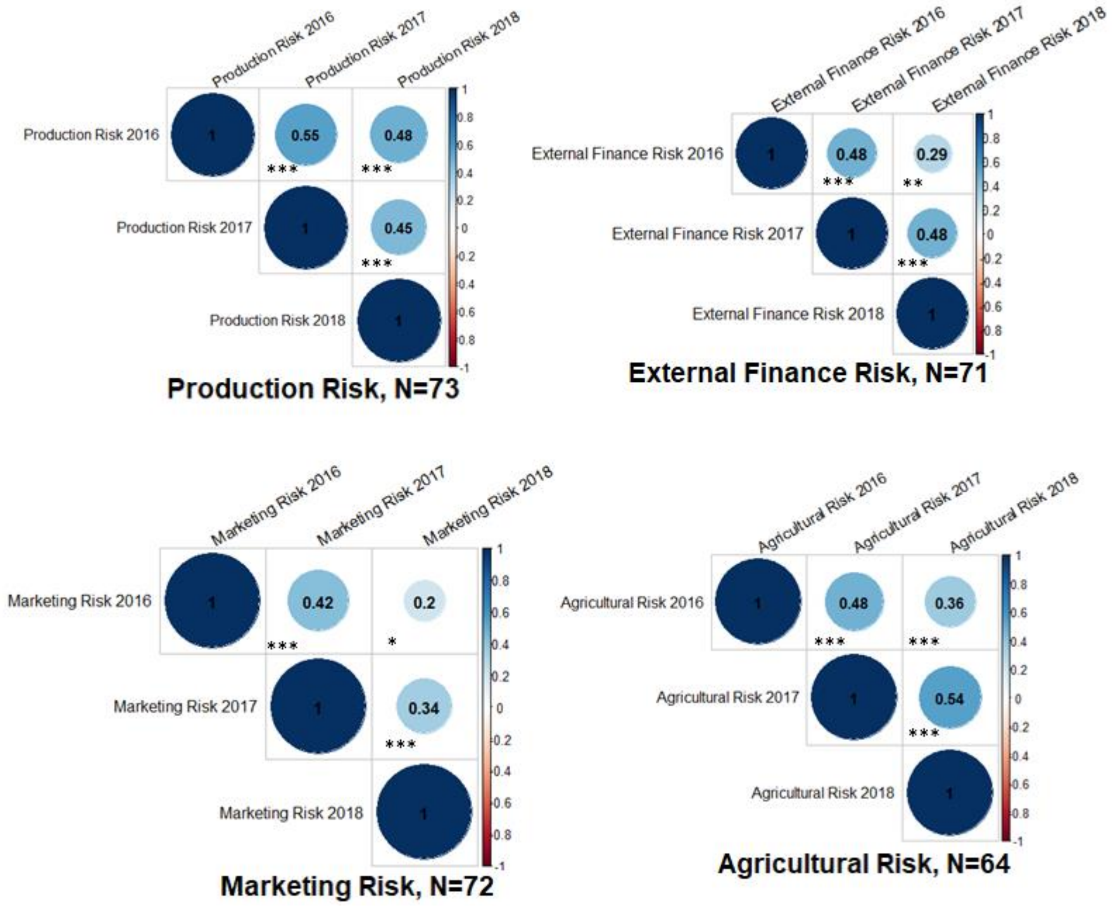


Figure 4. Correlations of risk preferences across years for each domain of risk preference

Note: ***, ** and * represent that the Null hypothesis of zero correlation is rejected at the 1%, 5% and 10% level of significance, respectively.

Next, we focus on the role of experiencing shocks in explaining the observed variation of risk preferences over time. Figure 5 shows a coefficient plot for the results of the regressions investigating the effect of shocks on change in risk preferences. The coefficients for frost and Drosophila suzukii come from the model shown in Equation 1. The interaction term comes from the model shown in Equation 2. The full regression results can be found in Appendix C.

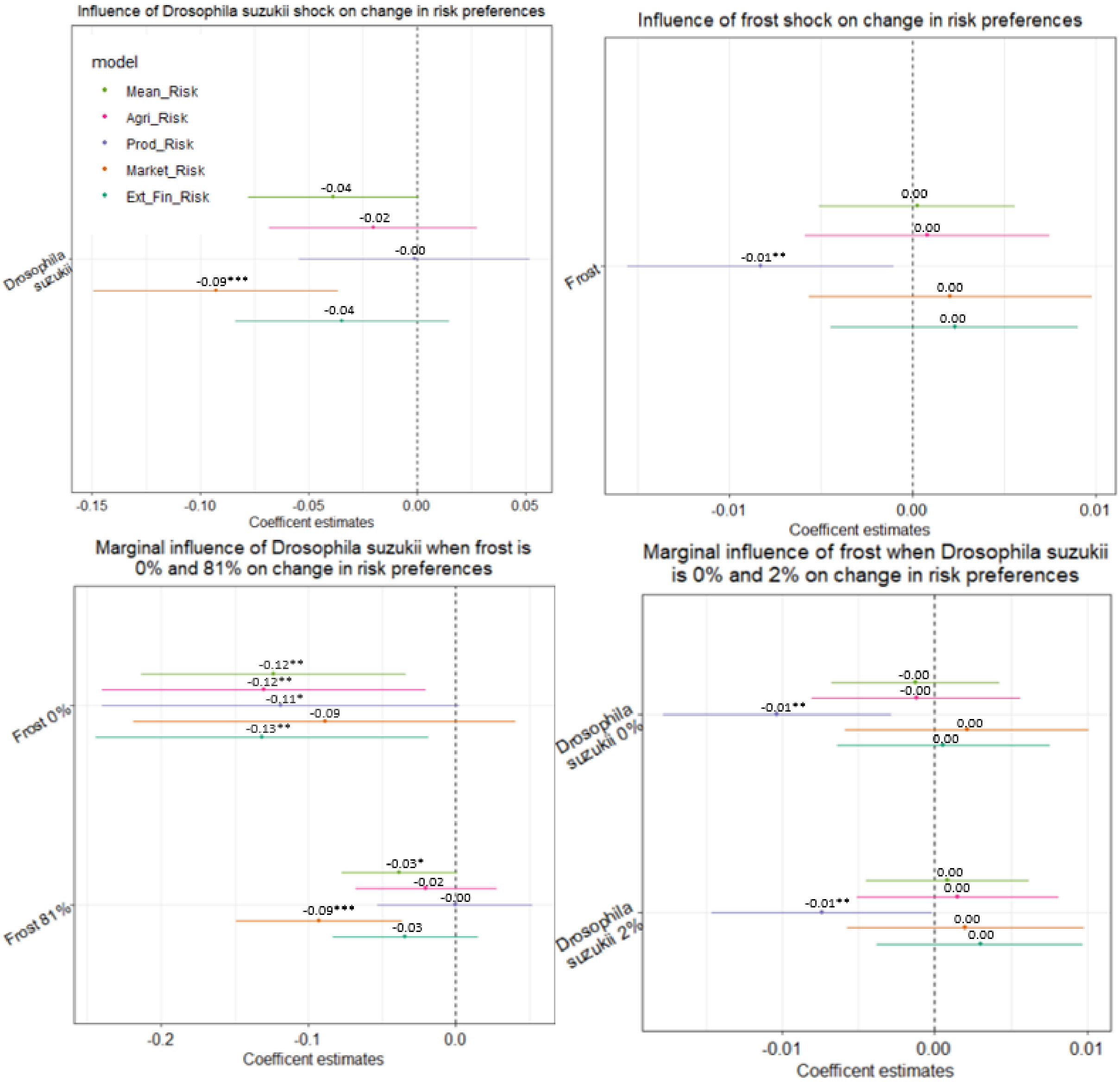
The upper left panel of Figure 5 shows that frost only has an effect on risk attitudes in the production domain. Presented marginal effects show the effect of a 1-unit increase (1 percentage point) in crop damage by frost decreases the change in risk preferences by 0.008. Thus, a 100-percentage point change in frost damage would decrease the change in risk preferences by 0.8 (less than one point on the scale), which represents only small effect. The sign of the effect indicates that farmers tend to become more risk loving after experiencing frost shocks. Furthermore, frost damage has no significant effect for the average of risk preferences or in the marketing, agriculture or financing domain (Figure 5).

The upper right panel of Figure 5 shows the share of crop damaged by Drosophila suzukii only affects marketing risk attitudes. Presented marginal effects show the effect of a 1-unit increase (1 percentage point) in crop damage due to Drosphila suzukii decreases the change in marketing risk attitudes by 0.091. Thus, a 10-percentage point change in pest damage would decrease the change in risk preferences by 0.91 (less than one point on the scale). Again, the sign of the effect indicates that farmers tend to become more risk loving after experiencing pest shocks. Drosophila suzukii damage does not affect risk preferences in any other domain.

Next, we investigate the role of the interaction of both shocks. Thus, we investigate the effect of experiencing both shocks in the same year on farmer risk preferences. When the two shocks are interacted (Equation 2), there is an effect for the mean of risk preferences and for risk preferences in the agricultural and production domain (see results in Appendix C). To understand this interaction effect, we estimate and present the marginal effects while holding one shock constant. In the bottom left coefficient plot, we plot the average marginal effect for Drosophila suzukii when holding frost damage at 0% and at 81%, these are the 25th and 75th percentile when the 2017 and 2018 data is pooled. In the bottom right coefficient plot, we plot the average marginal effect of frost damage when holding Drosophila suzukii damage at 0% and at 2%. Additionally, we also plotted the marginal effects graphically, these can be found in Appendix D. Results suggest that simultaneous experience of climate and pest related crop damages causes farmers to be more risk loving in multiple domains. However, interaction between different shocks are not necessarily linear, e.g. joint experiencing of shocks in one year can reinforce or buffer more risk loving behavior, depending on their magnitude.

As robustness checks, we also provide estimations with fruit fixed effects, fruit and year fixed effects as well as farm and farmer characteristics. Results including fruit controls can be found in Appendix E, results including fruit and year can be found in Appendix F. Finally, we control for farm and farmer characteristics and these results can be found in Appendix G. Results are similar, but these results show DS*Frost interaction is only significant at 10% for mean and production risk. Agricultural risk is significant at 1%.

Figure 5. Coefficient plots for effect of shocks on risk preferences



Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Our regression analysis shows that the experience of extreme events that lead to production losses can partly explain the variation of risk preferences over time. Yet, a large part of this variation over time remains unexplained. Next to measurement noise, other shocks and other factors such as personality and cognitive ability may matter here (Jagelka 2020).

Conclusion

Using farmers' risk preference measurements across years and across elicitation methods for a sample of Swiss fruit and grapevine producers, we find that self-reported risk preferences across different domains correlate only weakly with findings from a Holt and Laury lottery. Moreover, self-reported risk preferences are moderately correlated from one year to another and weakly correlated across a two-year time span. The experiences of shocks, i.e. crop losses due to frost or pests, explains some variation across years. Farmers tend to become more risks loving after experiencing shocks. Our results thus reveal that farmer risk preferences are far from being stable as usually assumed in neoclassical economic theory.

This poses a challenge for the use of these results in economic and policy analyses. First, farmers' risk preferences may change dramatically and quickly over time. External influences (e.g. weather and market shocks, policy changes) may lead risk averse farmers to become less risk averse or even risk loving and vice versa. Policies relying on farmers being risk averse such as support of insurances may thus be rendered inefficient quickly. Note that *Schildberg-Hörisch (*2018) offers an alternative conceptual framework for preference stability that builds on research regarding the stability of personality traits in psychology. Second, policies should not rely on risk preferences derived from a single elicitation method. In contrast, the predictive validity, i.e. the extent to which a method and underlying psychological trait has power in forecasting behavior, should receive larger attention in policy analysis. For example, Rommel et al. (2019) show that lottery tasks have only a low ability to predict risk-taking of farmers in production and crop insurance decisions.

Our findings reveal that future research should use multiple elicitation methods simultaneously to elicit risk preferences. It especially highlights the necessity for domain-specific risk preference elicitation and the necessity for repeated measurement. Here, a wide range of experimental approaches (e.g. other lottery tasks than the Holt and Laury lottery) shall be used (see e.g. Charness et al. 2013, and Iyer et al. (2020) for overviews). Moreover, much more emphasis should be placed on the predictive validity of risk preferences compared to the sheer reporting of risk preferences alone. Systematic reviews and meta-analyses of farmer risk preferences should receive further attention. The landscape of farmer risk preference elicitation remains scattered, i.e. different methods are applied to specific samples usually in one point of time. More coordinated efforts that allow comparable observations across space (countries, farm types etc.) and longer time periods are needed to better understand farmers' risk preferences. See Falk et al. (2018) for a global overview of economic preferences (for non-farming communities). Such exercises may also be expanded to incorporate other economic preferences (e.g. time preferences) and behavioral factors such as culture and personality traits (cp. Knapp et al., 2021, Wuepper, 2020, Boyce et al 2019).

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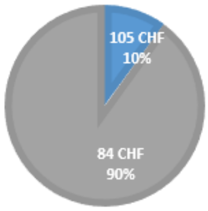
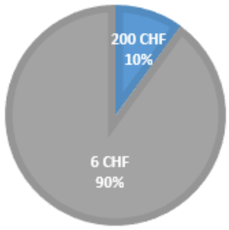
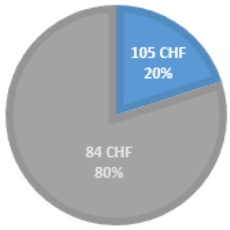
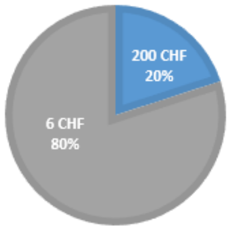
Online Appendices A- G

Appendix A – used risk preference elicitation tasks

A1 - Used Multiple Price List (Holt and Laury lottery) to elicit risk preferences

"You can decide between two insecticides against the *Drosophila suzukii*, A and B. Consider that the overall costs, the payment time, the difficulty in handling the insecticide, the safety of the insecticide for the consumers and farmers are the same for insecticide A and insecticide B. Insecticide A has a more stable economic return than B, given that it has been longer on the market and we can better predict the probability of the economic return. Insecticide B is new on the market; it has a less predictable economic return but reveals itself to be in some cases extremely efficient and thus provides you at times higher economic returns. Below in the table, there are 10 different scenarios. You are asked to choose either A or B. Note that no choice is right or wrong and all depends on your personal preferences.". Participants were asked to make 10 distinct choices, so we did not enforce one single switching point. This raises also concerns of inconsistent responses, e.g. if people reveal multiple switching points, or never switch (see e.g. Meraner et al. 2018). However, in our sample there are only XXX respondents with inconsistent responses. We removed thee for our analysis of the Holt and Laury lottery.

The design and specification of the lottery task follows closely the initial setup proposed by Holt and Laury (2002). Concerning the illustration of the lottery and the design of the lottery, we followed Meraner and Finger (2017). Participants received clear instructions, also on mechanisms of rewad. Overall, 10% of the participants have been selected as winners. For those 10% of participants, one of the 10 scenario was randomly drawn and played for real. The minimum that selected participants could win was 6 CHF and the maximum was 200 CHF. The compensation scheme was chosen to represent that expected return for each producer participating in the survey was 15 CHF. As participation in the overall survey took ca. 20 minutes, this reflects an hourly compensation of 45 CHF in line with Swiss wage levels. Winners of the lotteries were contacted via email and money was transferred a few days after the participation in the survey. See also Knapp et al., 2019, for further details.

	Insecticide A	**Insecticide B**
Scenario 1	☐ 10% probability of economic return 105 CHF and 90% probability of economic return 84 CHF 	☐ 10% probability of an economic return 200 CHF and 90% of an economic return 6 CHF 
Scenario 2	☐ 20% probability of an economic return 105 CHF and 80% probability of an economic return 84 CHF 	☐ 20 % probability of an economic return 200 CHF and 80% probability of an economic return 6 CHF 

The number of safe choices and associated Arrow-Pratt coefficient of relative risk aversion (CRRA) under Expected Utility Theory following Holt and Laury (2002)

Number of safe choices	**Range of relative risk aversion for the follow owing utility function $U(x) = x^{1-r}/(1-r)$**	**Riks Preference Classification following Holt and Laury (2022)**
0-1	< -0.98	Highly risk loving
2	-0.98 to -0.51	Very risk loving
3	-0.51 to -0.16	Risk loving
4	-0.16 to 0.14	Risk neutral
5	0.14 to 0.41	Slightly risk averse
6	0.41 to 0.69	Risk averse
7	0.69 to 0.99	Very risk averse
8	0.99 to 1.4	Highly risk averse
9-10	>1.4	Stay in bed

A2 - Used domain specific self-stated risk preferences

Domain specific self-stated risk preferences were measured via Likert type contextualized self-assessment questions on attitude to risk taking in four different domains, namely production, market and prices, external financing and agriculture in general, following Dohmen et al. (2011), Weber et al. (2002), and Meuwissen et al., (2001). Participants were asked to choose a value from 0= not willing to take a risk at all to 10=very willing to take a risk in the chosen domain following [3].

Please indicate on the scale below. The value of 0 stands for "not willing to take a risk at all" and the value 10 for "very willing to take a risk". With the values in between you can grade your assessment.

Production	not willing										very willing
	0	1	2	3	4	5	6	7	8	9	10
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Market and prices	not willing										very willing
	0	1	2	3	4	5	6	7	8	9	10
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
External financing	not willing										very willing
	0	1	2	3	4	5	6	7	8	9	10
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Agriculture in general	very willing										very willing
	0	1	2	3	4	5	6	7	8	9	10
	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Appendix B – Summary statistics

Table B1. Summary statistics of experienced shocks

Variable	Description	Year	Mean	Obs.	s.d	Min	Max
DS100	Proportion of crop affected by Drosophila suzukii from 0% to 100%.	2016	2.248	191	8.702	0.000	100.000
		2017	1.834	245	6.525	0.000	87.500
		2018	0.936	227	1.843	0.000	18.750
Frost100	Proportion of crop affected by frost (either partially or fully) from 0% to 100%.	2016	N/A	N/A	N/A	N/A	N/A
		2017	52.370	245	46.335	0.000	100.000
		2018	2.990	227	14.646	0.000	100.000
DS0	=1 if their crop was affected by Drosophila suzukii	2016	0.644	191	0.480	0.000	1.000
		2017	0.461	245	0.500	0.000	1.000
		2018	0.423	227	0.495	0.000	1.000
Frost Max	=1 if farmer has experienced frost (either part or full damage) for at least one variety	2016	N/A	N/A	N/A	N/A	N/A
		2017	0.612	245	0.488	0.000	1.000
		2018	0.062	227	0.241	0.000	1.000

Table B2. Summary statistics of risk preferences

Variable	**Description**	**Year**	**NAs**	**Obs**	**Mean**	**s.d**	**Min**	**Max**
Agri_risk	Willingness to take risks in agriculture in general =0 very willing to =10 very unwilling.	2016	0	191	6.047	2.890	0.000	10.000
		2017	0	245	5.608	2.615	0.000	10.000
		2018	29	198	5.157	2.715	0.000	10.000
Marketing_risk	Willingness to take risks in marketing =0 very willing to =10 very unwilling.	2016	0	191	5.974	2.816	0.000	10.000
		2017	0	245	5.657	2.466	0.000	10.000
		2018	11	216	5.310	2.868	0.000	10.000
Ext_fin_risk	Willingness to take risks in external financing =0 very willing to =10 very unwilling.	2016	0	191	7.398	2.905	0.000	10.000
		2017	0	245	7.396	2.626	0.000	10.000
		2018	12	215	6.995	2.577	0.000	10.000
Prod_risk	Willingness to take risks in production =0 very willing to =10 very unwilling.	2016	0	191	5.613	2.916	0.000	10.000
		2017	0	245	4.873	2.662	0.000	10.000
		2018	1	226	5.173	2.734	0.000	10.000
Mean_risk	Average of willingness to take risks in production, agriculture, external financing and marketing. =0 very willing to =10 very unwilling.	2016	0	191	6.258	2.489	0.000	10.000
		2017	0	245	5.884	2.082	0.000	10.000
		2018	0	227	5.592	2.245	0.000	10.000
HLsafe	Number of safe choices in the holt and laury lottery task	2018	100	127	5.496	2.507	0.000	10.000

Table B3. Summary statistics of change in risk preferences between years

Variable	Description	Year	NAs	Obs	Mean	s.d	Min	Max
Agri_risk_ch	Change in agriculture risk preferences from the previous year, >0 risk aversion increased, =0 remained the same, <0 risk aversion decreased	2017	105	140	-0.150	2.703	-8.000	10.000
		2018	30	149	0.047	2.261	-6.000	10.000
Marketing_risk_ch	Change in marketing risk preferences from the previous year, >0 risk aversion increased, =0 remained the same, <0 risk aversion decreased	2017	105	140	-0.371	2.904	-10.000	10.000
		2018	16	163	-0.209	3.021	-9.000	10.000
Ext_fin_risk_ch	Change in agriculture external finance risk preferences from the previous year, >0 risk aversion increased, =0 remained the same, <0 risk aversion decreased .	2017	105	140	0.000	2.645	-8.000	10.000
		2018	16	163	-0.258	2.488	-8.000	6.000
Prod_risk_ch	Change in production risk preferences from the previous year, >0 risk aversion	2017	105	140	-0.621	2.604	-9.000	10.000
		2018	9	170	0.506	2.816	-9.000	10.000

	increased, =0 remained the same, <0 risk aversion decreased							
Mean_risk_ch	Change in mean risk preferences from the previous year, >0 risk aversion increased, =0 remained the same, <0 risk aversion decreased	2017	105	140	-0.286	2.114	-8.250	7.500
		2018	8	171	-0.096	2.261	-6.000	7.500

Appendix C – Estimation results

Table C1**.** Ordinary Least Square regression for the effect of shocks on mean risk change

	Dependent variable:			
	Mean_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	-0.0004		0.0002	-0.001
	(0.003)		(0.003)	(0.003)
DS100		-0.038	-0.039	-0.124***
		(0.057)	(0.057)	(0.030)
Frost100:DS100				0.001***
				(0.0004)
Constant	-0.169	-0.122	-0.129	-0.034
	(0.142)	(0.135)	(0.153)	(0.145)
Observations	311	311	311	311
R^2	0.0001	0.012	0.012	0.025
Adjusted R^2	-0.003	0.009	0.006	0.016

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table C2**.** Ordinary Least Square regression for the effect of shocks on agricultural risk change

	Dependent variable:			
	Agri_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	0.0004		0.001	-0.001
	(0.004)		(0.004)	(0.004)
DS100		-0.020	-0.020	-0.130***
		(0.053)	(0.053)	(0.029)
Frost100:DS100				0.001***
				(0.001)
Constant	-0.062	-0.017	-0.040	0.086
	(0.171)	(0.161)	(0.179)	(0.175)
Observations	289	289	289	289
R^2	0.0001	0.002	0.002	0.019
Adjusted R^2	-0.003	-0.001	-0.004	0.008

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table C3**.** Ordinary Least Square regression for the effect of shocks on production risk change

	Dependent variable:			
	Prod_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	-0.008**		-0.008**	-0.010***
	(0.003)		(0.003)	(0.003)
DS100		-0.009	-0.001	-0.119*
		(0.080)	(0.079)	(0.062)
Frost100:DS100				0.001**
				(0.001)
Constant	0.240	0.011	0.241	0.370*
	(0.194)	(0.184)	(0.211)	(0.205)
Observations	310	310	310	310
R^2	0.016	0.0004	0.016	0.031
Adjusted R^2	0.013	-0.003	0.010	0.021

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table C4. Ordinary Least Square regression for the effect of shocks on marketing risk change

	Dependent variable:			
	Mkt_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	0.0005		0.002	0.002
	(0.004)		(0.004)	(0.004)
DS100		-0.091***	-0.093***	-0.089
		(0.012)	(0.013)	(0.093)
Frost100:DS100				-0.00005
				(0.001)
Constant	-0.297	-0.142	-0.201	-0.205
	(0.208)	(0.173)	(0.207)	(0.222)
Observations	303	303	303	303
R^2	0.00004	0.033	0.034	0.034
Adjusted R^2	-0.003	0.029	0.027	0.024

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table C5. Ordinary Least Square regression for the effect of shocks on external financing risk change

	Dependent variable:			
	Ext_Fin_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	0.002		0.002	0.001
	(0.003)		(0.003)	(0.004)
DS100		-0.033	-0.035	-0.131***
		(0.083)	(0.084)	(0.027)
Frost100:DS100				0.001
				(0.001)
Constant	-0.189	-0.088	-0.153	-0.047
	(0.178)	(0.178)	(0.199)	(0.187)
Observations	303	303	303	303
R^2	0.001	0.006	0.007	0.018
Adjusted R^2	-0.003	0.002	0.0005	0.009

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Appendix D – Predicted values of (mean) changes in risk preferences

Figure D1. Predicted values of mean risk change for levels of frost and Drosophila Suzukii

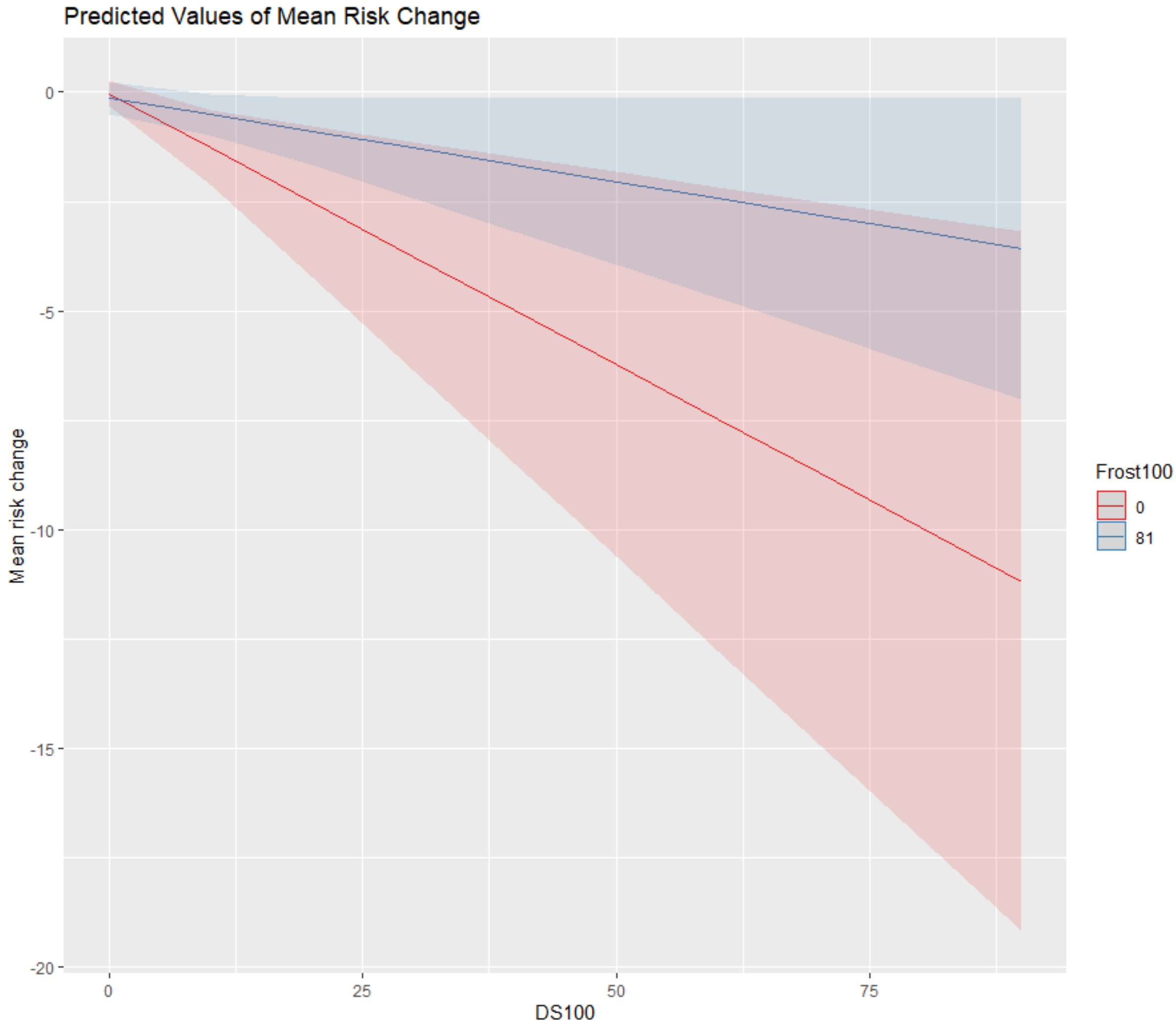


Figure D2. Predicted values of production risk change for levels of frost and Drosophila Suzukii

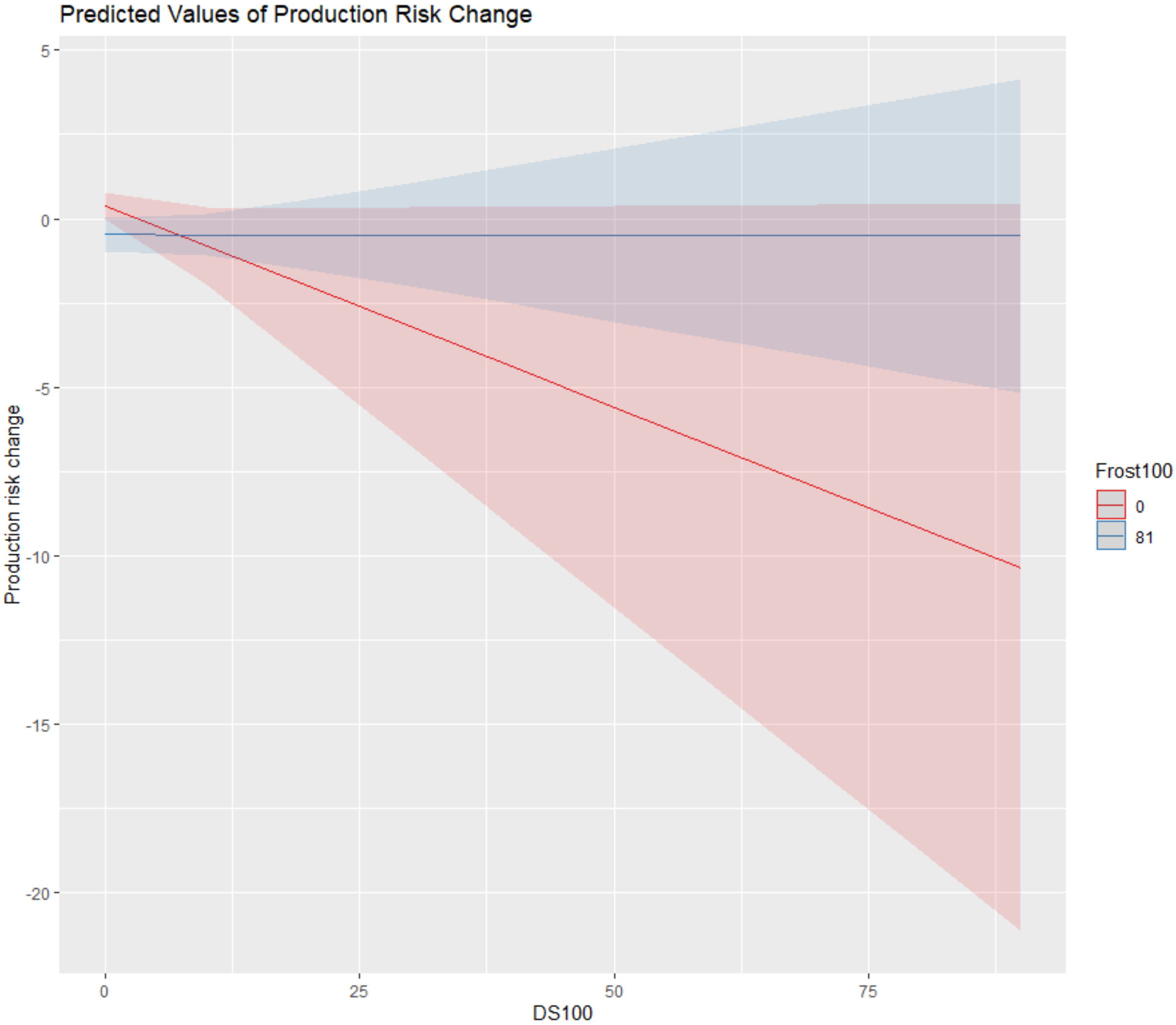


Figure D3. Predicted values of agricultural risk change for levels of frost and Drosophila Suzukii

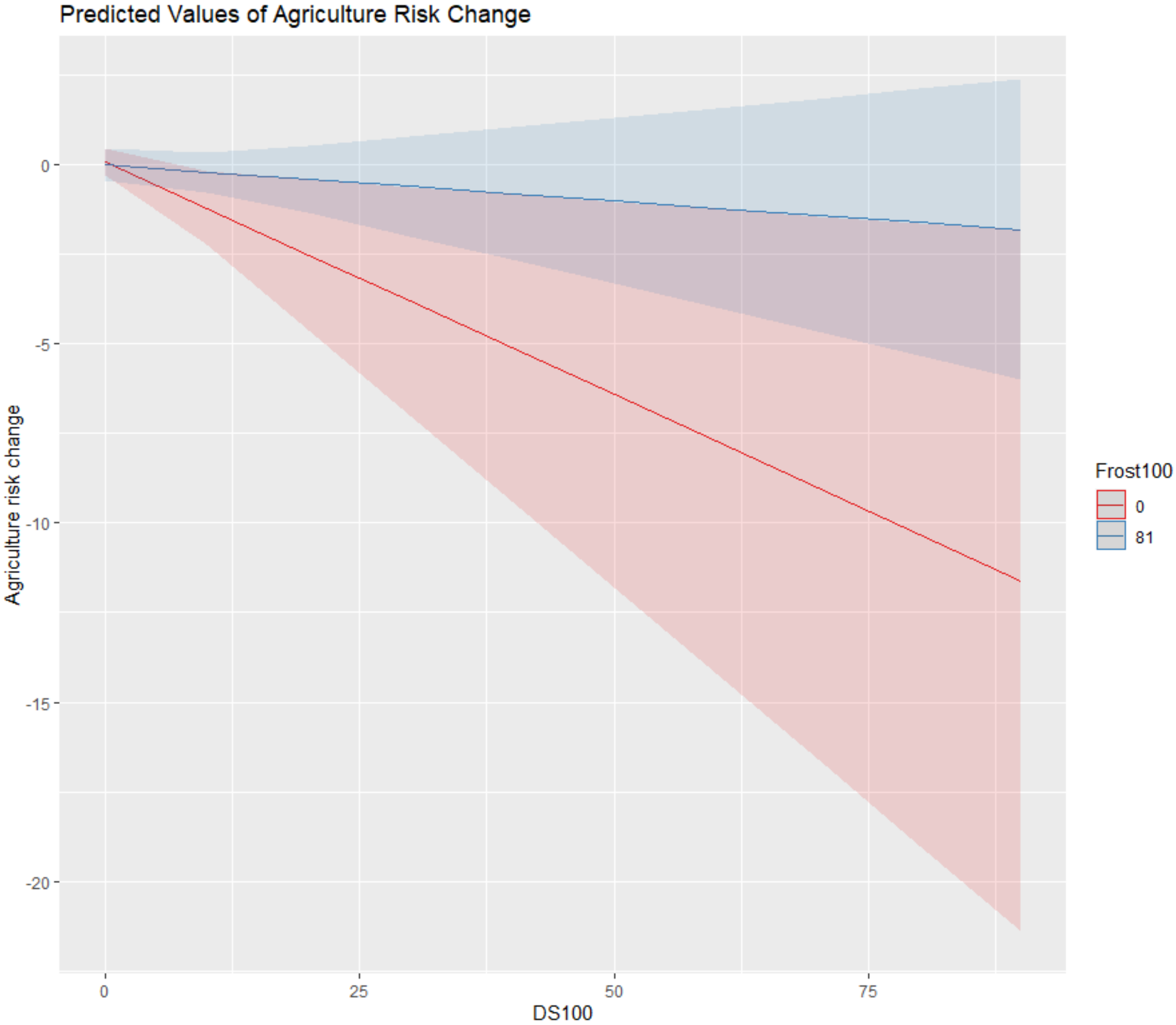


Figure D4. Predicted values of marketing risk change for levels of frost and Drosophila Suzukii

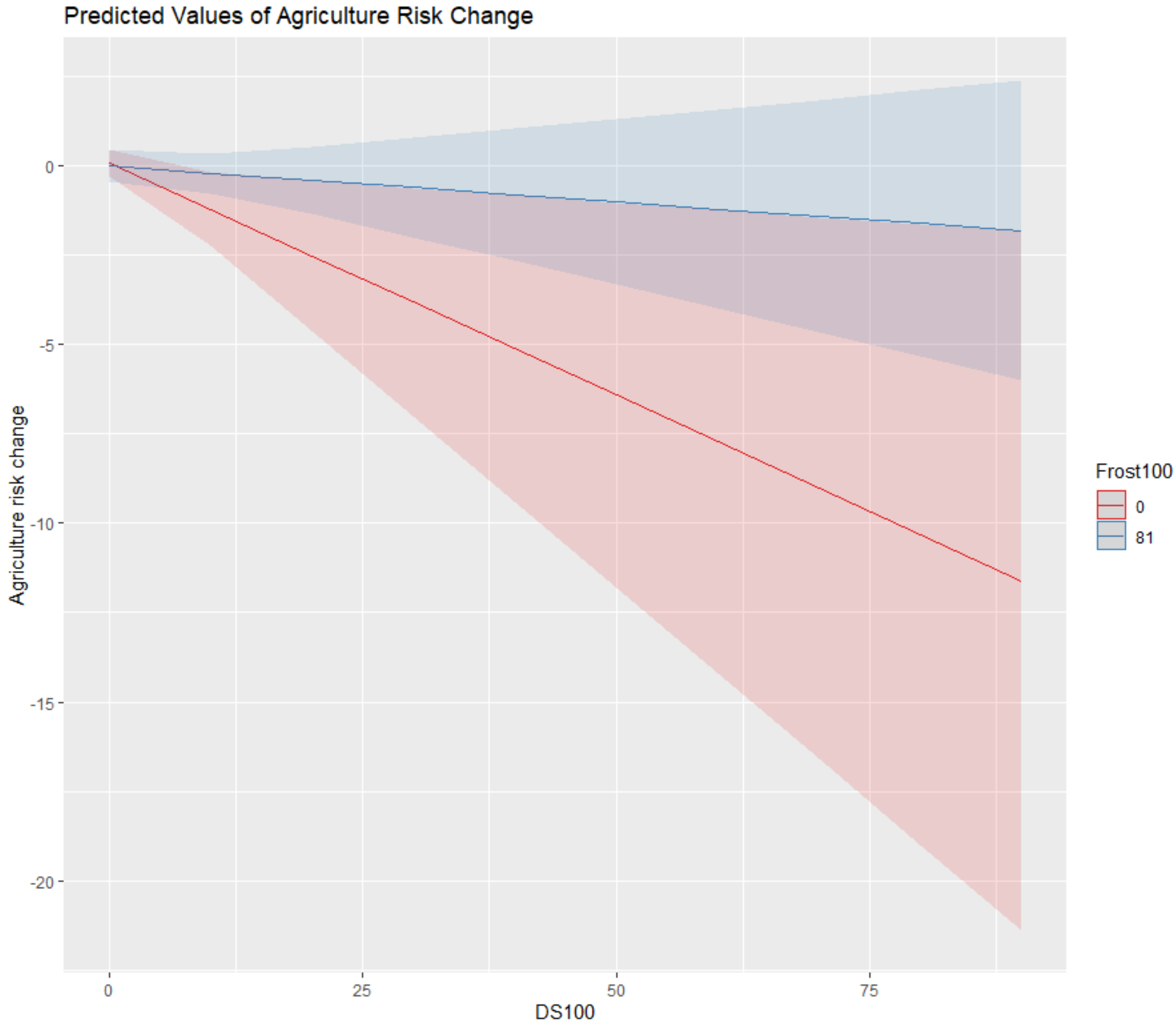
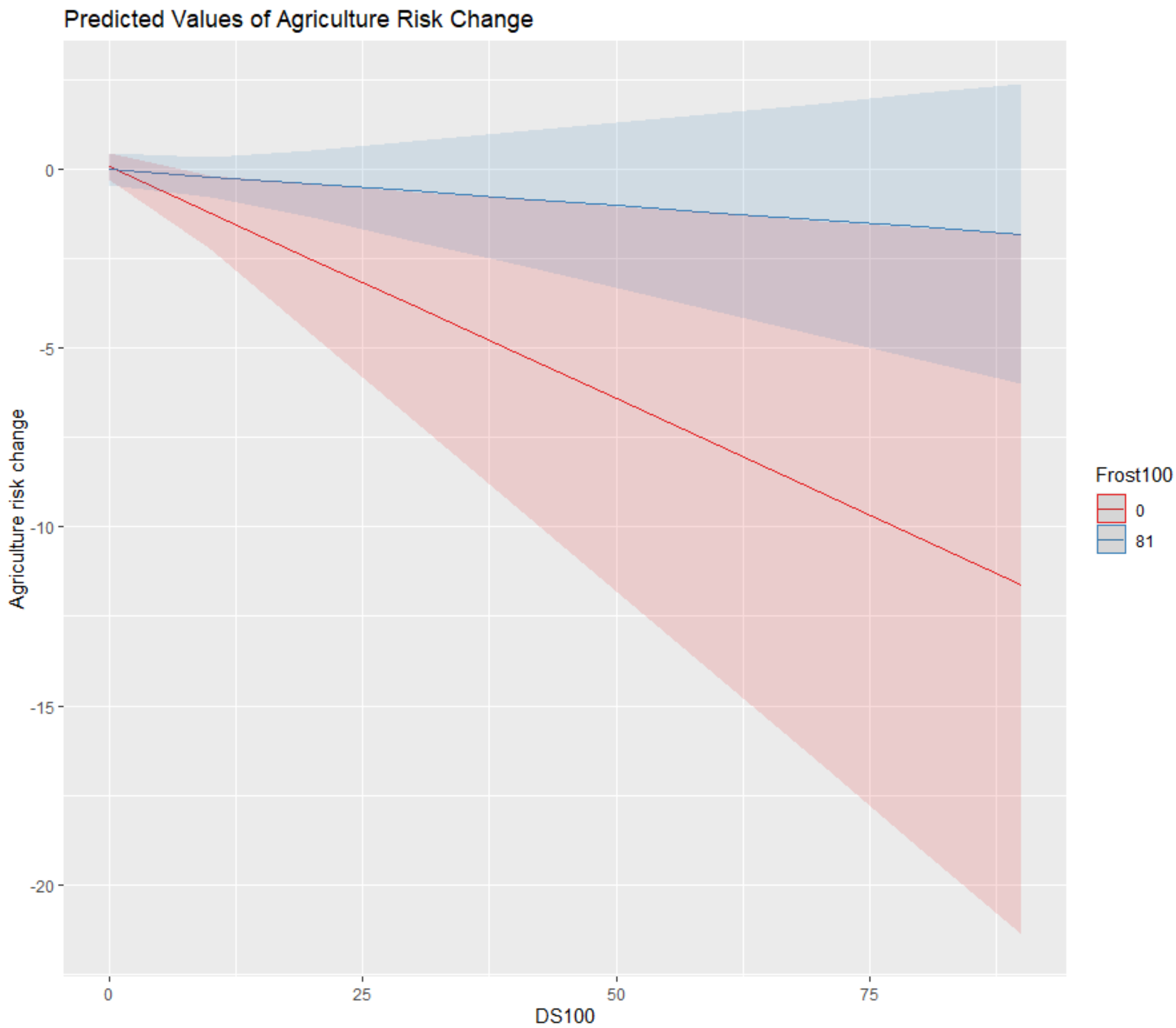


Figure D5. Predicted values of external financing risk change for levels of frost and Drosophila Suzukii



Appendix E – Estimation results with fruit fixed effects

Table E1. Ordinary Least Square regression for the effect of shocks on mean risk change (fruit included)

	Dependent variable:			
	Mean_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	-0.0002		0.0004	-0.001
	(0.003)		(0.003)	(0.003)
DS100		-0.038	-0.039	-0.123***
		(0.057)	(0.058)	(0.031)
fruitgrapes	-0.126	-0.076	-0.088	-0.020
	(0.246)	(0.238)	(0.250)	(0.246)
fruitplums	-0.178	-0.158	-0.173	-0.084
	(0.318)	(0.296)	(0.320)	(0.320)
Frost100:DS100				0.001***
				(0.0004)
Constant	-0.054	-0.041	-0.042	-0.009
	(0.178)	(0.178)	(0.178)	(0.175)
Observations	311	311	311	311
R^2	0.001	0.012	0.012	0.026
Adjusted R^2	-0.009	0.003	-0.0005	0.010

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table E2. Ordinary Least Square regression for the effect of shocks on agricultural risk change (fruit included)

	Dependent variable:			
	Agri_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	0.0003		0.001	-0.002
	(0.004)		(0.004)	(0.004)
DS100		-0.021	-0.022	-0.133***
		(0.055)	(0.055)	(0.029)
grapes	0.150	0.194	0.174	0.273
	(0.326)	(0.316)	(0.329)	(0.327)
plums	-0.074	-0.047	-0.072	0.047
	(0.388)	(0.375)	(0.390)	(0.392)
Frost100:DS100				0.001***
				(0.0005)
Constant	-0.157	-0.149	-0.150	-0.107
	(0.246)	(0.246)	(0.247)	(0.245)
Observations	330	330	330	330
R^2	0.0004	0.002	0.002	0.012
Adjusted R^2	-0.009	-0.008	-0.010	-0.003

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table E3. Ordinary Least Square regression for the effect of shocks on production risk change (fruit included)

	Dependent variable:			
	Prod_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	-0.008**		-0.008**	-0.010***
	(0.003)		(0.004)	(0.004)
DS100		-0.008	-0.001	-0.118*
		(0.079)	(0.078)	(0.065)
grapes	-0.211	-0.430	-0.210	-0.117
	(0.512)	(0.508)	(0.517)	(0.513)
plums	-0.249	-0.526	-0.249	-0.126
	(0.609)	(0.595)	(0.611)	(0.612)
Frost100:DS100				0.001**
				(0.001)
Constant	0.424	0.409	0.425	0.470
	(0.465)	(0.466)	(0.465)	(0.465)
Observations	310	310	310	310
R^2	0.017	0.003	0.017	0.031
Adjusted R^2	0.007	-0.007	0.004	0.015

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table E4. Ordinary Least Square regression for the effect of shocks on marketing risk change (fruit included)

	Dependent variable:			
	Market_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	0.001		0.002	0.002
	(0.004)		(0.004)	(0.004)
DS100		-0.092***	-0.094***	-0.089
		(0.012)	(0.013)	(0.097)
grapes	-0.057	0.102	0.038	0.034
	(0.455)	(0.441)	(0.454)	(0.458)
plums	-0.275	-0.188	-0.268	-0.273
	(0.583)	(0.547)	(0.583)	(0.588)
Frost100:DS100				-0.0001
				(0.001)
Constant	-0.220	-0.187	-0.191	-0.193
	(0.387)	(0.386)	(0.387)	(0.388)
Observations	303	303	303	303
R^2	0.001	0.034	0.035	0.035
Adjusted R^2	-0.009	0.024	0.022	0.019

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table E5. Ordinary Least Square regression for the effect of shocks on external financing risk change (fruit included)

	Dependent variable:			
	Ext_Fin_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	0.001		0.002	0.0001
	(0.004)		(0.004)	(0.004)
DS100		-0.033	-0.034	-0.134***
		(0.085)	(0.085)	(0.028)
grapes	0.046	0.138	0.080	0.160
	(0.363)	(0.356)	(0.370)	(0.364)
plums	0.240	0.314	0.242	0.344
	(0.449)	(0.441)	(0.452)	(0.455)
Frost100:DS100				0.001
				(0.001)
Constant	-0.253	-0.239	-0.243	-0.204
	(0.292)	(0.292)	(0.292)	(0.287)
Observations	303	303	303	303
R^2	0.002	0.007	0.008	0.020
Adjusted R^2	-0.008	-0.003	-0.006	0.003

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Appendix F – Estimation results with fruit and year fixed effects

Table F1. Ordinary Least Square regression for the effect of shocks on mean risk change (fruit and year included)

	Dependent variable:			
	Mean_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	0.002		0.002	0.0004
	(0.004)		(0.004)	(0.004)
DS100		-0.037	-0.038	-0.120***
		(0.057)	(0.056)	(0.031)
fruitgrapes	-0.045	-0.011	-0.012	0.035
	(0.264)	(0.267)	(0.267)	(0.263)
fruitplums	-0.097	-0.086	-0.097	-0.030
	(0.336)	(0.334)	(0.336)	(0.333)
year	0.287	0.135	0.271	0.203
	(0.363)	(0.259)	(0.361)	(0.360)
Frost100:DS100				0.001**
				(0.0004)
Constant	-579.693	-272.300	-546.940	-409.637
	(732.700)	(523.317)	(728.088)	(726.718)
Observations	311	311	311	311
R^2	0.003	0.013	0.015	0.027
Adjusted R^2	-0.010	0.0004	-0.001	0.008

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table F2. Ordinary Least Square regression for the effect of shocks on agricultural risk change (fruit and year included)

	Dependent variable:			
	Agri_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	0.003		0.004	0.001
	(0.005)		(0.005)	(0.005)
DS100		-0.020	-0.021	-0.128***
		(0.054)	(0.053)	(0.030)
fruitgrapes	0.291	0.315	0.312	0.380
	(0.347)	(0.350)	(0.350)	(0.346)
fruitplums	0.062	0.081	0.061	0.150
	(0.412)	(0.411)	(0.413)	(0.411)
year	0.441	0.228	0.434	0.351
	(0.443)	(0.327)	(0.445)	(0.441)
Frost100:DS100				0.001***
				(0.0005)
Constant	-890.555	-460.305	-875.856	-708.862
	(893.771)	(659.966)	(898.306)	(889.364)
Observations	289	289	289	289
R^2	0.006	0.006	0.008	0.023
Adjusted R^2	-0.008	-0.008	-0.009	0.002

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table F3. Ordinary Least Square regression for the effect of shocks on production risk change (fruit and year included)

	Dependent variable:			
	Prod_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	0.003		0.004	0.001
	(0.005)		(0.005)	(0.005)
DS100		-0.020	-0.021	-0.128***
		(0.054)	(0.053)	(0.030)
fruitgrapes	0.291	0.315	0.312	0.380
	(0.347)	(0.350)	(0.350)	(0.346)
fruitplums	0.062	0.081	0.061	0.150
	(0.412)	(0.411)	(0.413)	(0.411)
year	0.441	0.228	0.434	0.351
	(0.443)	(0.327)	(0.445)	(0.441)
Frost100:DS100				0.001***
				(0.0005)
Constant	-890.555	-460.305	-875.856	-708.862
	(893.771)	(659.966)	(898.306)	(889.364)
Observations	289	289	289	289
R^2	0.006	0.006	0.008	0.023
Adjusted R^2	-0.008	-0.008	-0.009	0.002

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table F4. Ordinary Least Square regression for the effect of shocks on marketing risk change (fruit and year included)

	Dependent variable:			
	Mkt_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	0.003		0.004	0.005
	(0.005)		(0.005)	(0.005)
DS100		-0.091***	-0.093***	-0.084
		(0.013)	(0.013)	(0.095)
fruitgrapes	0.043	0.128	0.126	0.121
	(0.484)	(0.485)	(0.485)	(0.487)
fruitplums	-0.176	-0.159	-0.180	-0.188
	(0.605)	(0.599)	(0.603)	(0.607)
year	0.338	0.053	0.299	0.307
	(0.486)	(0.373)	(0.482)	(0.488)
Frost100:DS100				-0.0001
				(0.001)
Constant	-682.258	-107.008	-603.941	-619.272
	(980.819)	(752.944)	(973.012)	(984.576)
Observations	303	303	303	303
R^2	0.003	0.034	0.036	0.036
Adjusted R^2	-0.011	0.021	0.020	0.017

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table F5. Ordinary Least Square regression for the effect of shocks on external finance risk change (fruit and year included)

	Dependent variable:			
	Ext_Fin_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	-0.001		-0.0002	-0.003
	(0.005)		(0.005)	(0.005)
DS100		-0.035	-0.035	-0.140***
		(0.087)	(0.087)	(0.029)
fruitgrapes	-0.040	-0.010	-0.009	0.049
	(0.383)	(0.388)	(0.388)	(0.381)
fruitplums	0.155	0.152	0.153	0.235
	(0.474)	(0.475)	(0.475)	(0.476)
year	-0.291	-0.296	-0.306	-0.394
	(0.429)	(0.327)	(0.425)	(0.427)
Frost100:DS100				0.001
				(0.001)
Constant	586.570	597.502	617.032	795.715
	(866.530)	(660.176)	(858.607)	(861.474)
Observations	303	303	303	303
R^2	0.003	0.010	0.010	0.023
Adjusted R^2	-0.010	-0.004	-0.007	0.003

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Appendix G – Estimation results with farm and farmer characteristics

Table G1. Ordinary Least Square regression for the effect of shocks on mean risk change (farm and farmer characteristics included)

	Dependent variable:			
	Mean_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	0.00005		0.001	-0.001
	(0.003)		(0.003)	(0.003)
DS100		-0.040	-0.040	-0.131***
		(0.069)	(0.069)	(0.037)
Frost100:DS100				0.001*
				(0.001)
age	0.014	0.013	0.013	0.012
	(0.012)	(0.012)	(0.012)	(0.012)
male	0.386	0.097	0.088	-0.004
	(0.590)	(0.570)	(0.573)	(0.568)
farm area	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
french	0.089	0.027	0.031	-0.006
	(0.317)	(0.323)	(0.323)	(0.319)
italian	0.254	0.272	0.282	0.378
	(0.391)	(0.402)	(0.403)	(0.381)
Constant	-1.220	-0.800	-0.829	-0.584
	(0.796)	(0.735)	(0.770)	(0.764)
Observations	300	300	300	300
R^2	0.017	0.029	0.029	0.044
Adjusted R^2	-0.003	0.009	0.006	0.018

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table G2. Ordinary Least Square regression for the effect of shocks on agricultural risk change (farm and farmer characteristics included)

	Dependent variable:			
	Ag_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	0.001		0.002	-0.001
	(0.004)		(0.004)	(0.004)
DS100		-0.029	-0.030	-0.154***
		(0.070)	(0.070)	(0.031)
Frost100:DS100				0.002***
				(0.0003)
Age	0.009	0.008	0.008	0.007
	(0.015)	(0.014)	(0.015)	(0.015)
male	0.060	-0.162	-0.179	-0.326
	(0.716)	(0.705)	(0.705)	(0.663)
Farm area	-0.0002	-0.0002	-0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
french	-0.209	-0.267	-0.255	-0.307
	(0.363)	(0.375)	(0.372)	(0.366)
italian	0.168	0.156	0.185	0.310
	(0.548)	(0.565)	(0.560)	(0.545)
Constant	-0.414	-0.036	-0.100	0.267
	(0.956)	(0.887)	(0.926)	(0.902)
Observations	280	280	280	280
R^2	0.015	0.019	0.019	0.039
Adjusted R^2	-0.007	-0.003	-0.006	0.011

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table G3. Ordinary Least Square regression for the effect of shocks on production risk change (farm and farmer characteristics included)

	Dependent variable:			
	Prod_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	-0.008**		-0.008**	-0.010***
	(0.004)		(0.004)	(0.004)
DS100		-0.005	0.003	-0.116*
		(0.091)	(0.089)	(0.068)
Frost100:DS100				0.001*
				(0.001)
Age	0.011	0.013	0.011	0.009
	(0.016)	(0.016)	(0.016)	(0.017)
male	0.457	0.385	0.478	0.356
	(0.798)	(0.769)	(0.809)	(0.791)
Farm area	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0002)	(0.0002)	(0.0001)
french	0.118	0.168	0.122	0.075
	(0.434)	(0.443)	(0.442)	(0.439)
italian	0.186	0.291	0.184	0.312
	(0.543)	(0.553)	(0.565)	(0.537)
Constant	-0.724	-1.063	-0.752	-0.429
	(1.102)	(1.048)	(1.114)	(1.101)
Observations	299	299	299	299
R^2	0.022	0.008	0.022	0.036
Adjusted R^2	0.002	-0.012	-0.002	0.009

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table G4. Ordinary Least Square regression for the effect of shocks on marketing risk change (farm and farmer characteristics included)

	Dependent variable:			
	Mkt_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	0.002		0.004	0.004
	(0.004)		(0.004)	(0.004)
DS100		-0.096***	-0.099***	-0.105
		(0.025)	(0.027)	(0.086)
Frost100:DS100				0.0001
				(0.001)
Age	0.034*	0.031*	0.032*	0.032*
	(0.018)	(0.017)	(0.018)	(0.018)
male	0.677	-0.015	-0.061	-0.067
	(0.767)	(0.566)	(0.558)	(0.575)
Farm area	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
french	-0.018	-0.189	-0.167	-0.170
	(0.413)	(0.408)	(0.413)	(0.416)
italian	0.428	0.440	0.497	0.503
	(0.532)	(0.513)	(0.515)	(0.523)
Constant	-2.718**	-1.607*	-1.753*	-1.736*
	(1.118)	(0.940)	(0.967)	(0.970)
Observations	293	293	293	293
R^2	0.033	0.065	0.068	0.068
Adjusted R^2	0.013	0.046	0.045	0.042

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

Table G5. Ordinary Least Square regression for the effect of shocks on external financing risk change (farm and farmer characteristics included)

	Dependent variable:			
	Ext_Fin_Risk_Ch			
	(1)	(2)	(3)	(4)
Frost100	0.001		0.001	-0.0003
	(0.004)		(0.004)	(0.004)
DS100		-0.029	-0.031	-0.123***
		(0.085)	(0.086)	(0.035)
Frost100:DS100				0.001
				(0.001)
Age	0.011	0.010	0.010	0.009
	(0.015)	(0.015)	(0.015)	(0.015)
genderM	0.378	0.166	0.151	0.055
	(0.852)	(0.897)	(0.905)	(0.915)
surf_farm	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
french	0.009	-0.044	-0.035	-0.072
	(0.407)	(0.412)	(0.413)	(0.409)
italian	-0.322	-0.318	-0.300	-0.201
	(0.448)	(0.466)	(0.465)	(0.445)
Constant	-0.957	-0.610	-0.660	-0.411
	(1.072)	(1.109)	(1.129)	(1.139)
Observations	294	294	294	294
R^2	0.010	0.014	0.014	0.024
Adjusted R^2	-0.011	-0.007	-0.010	-0.003

Note: ***, ** and * represent that the Null hypothesis of zero effects of shocks on risk preferences is rejected at the 1%, 5% and 10% level of significance, respectively. Negative (positive) coefficients indicate that experiencing shocks leads to more risk loving (averse) behavior.

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